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The dynamic interrelation between external finance and bank credit

Fabrizio Casalin^{a*} and Enzo Dia^b

^a Newcastle University Business School, Newcastle upon Tyne, United Kingdom

^b Department of Economics and Quantitative Methods, University Bicocca, Milan, Italy

Abstract

This paper studies the interrelation among the volumes of bonds and stocks issued by non-financial firms, and levels of industrial loans outstanding in the US. These aggregates are co-integrated and characterized by asymmetric volatility. Their co-movements are driven by financial indicators such as the yield spread, size of loan market and market volatility. Bond and stock issuance are positively correlated, and even more so during the expansionary phase of the cycle. Loans outstanding and bond issuance are negatively correlated, and their substitutability increases in periods of economic downturn, highlighting the importance of bond markets to mitigate credit crunches.

Keywords: Security Issuance, Credit Market, Multivariate GARCH, Co-movement

JEL classification: C32, G01, G12

*Corresponding author. Email: fabrizio.casalin@newcastle.ac.uk.

I Introduction

As industrial firms grow, their increasing financial needs are satisfied by a combination of bank finance and resources raised in financial markets by issuing stocks or corporate bonds. In this work we analyze the behaviour over time of the aggregate volume of stocks and corporate bonds issued by non-financial firms, and commercial and industrial loans outstanding (C&I) in the United States. We use monthly data spanning from 1970 to 2012, providing information at the highest frequency available together with the dynamics of several business cycles to analyze to what extent these markets are interrelated over time, and influenced by macroeconomic shocks. In particular, we investigate whether the factors that influence the correlation between the returns or the liquidity across stock and Treasury bond markets can explain the the dynamic correlation among the aggregate quantities of financial flows available to industrial firms. The main questions we try to answer are the followings: Can bond finance mitigate the impact of a bank credit crunch, or, conversely, do loans substitute for bonds when corporate bond markets dry up? When interest rates rise sharply and unexpectedly, greatly reducing the volume of corporate bonds issued, does the availability of equity finance increase, smoothing the impact of such shocks on the system? To what extent do the different markets co-move following economic downturns and the occurrence of exogenous financial shocks?

We study reduced form equations by estimating a Vector Error Correction Model, finding that the three aggregates evolve into one co-integrating relation-

ship, with the issuance of stocks which is weakly exogenous. We find that such relationship is not stable over time, and that our empirical results are mainly driven by the last 20 years of the sample period under scrutiny. We then shed light on the level of co-movement among the three aggregates by using multivariate GARCH models. In line with the results obtained for secondary markets, this last is time-varying, and the conditional volatility of primary markets characterized by strong spill-over effects and asymmetric responses to positive and negative shocks.

We finally regress the conditional correlations among the three markets against macroeconomic and financial indicators, as well as a set of dummy variables to capture some specific episodes which have characterized the period under analysis. The correlation coefficients are well explained by indicators such as the yield spread, the volatility of stock and bond markets, and the ratio between bank credit and GDP. We find that the amount of finance raised in bond and stock markets is positively correlated over time, and even more so when financial markets expect an expansionary phase of the cycle. On the contrary, C&I loans and bond issuance are negatively correlated, and such negative linkage becomes even stronger in periods of economic downturn. Thus, the capability of the corporate bond market to compensate shocks that have a negative impact on the availability of bank credit rises in periods of distress. Finally, equity finance and C&I loans are loosely inter-related, although their correlation remains negative over the entire sample period.

The remainder of the paper is organized as follows. Section II reviews the relevant literature, whereas Section III introduces the dataset and reports some preliminary statistics. Sections IV describes the empirical methodologies used.

Sections V discusses the empirical results, while Section VI concludes the paper.

II Literature review

The respective role of market and bank finance to smooth shocks over time has been studied theoretically by Allen and Gale (1997). Other studies such as De Fiore and Uhlig (2011) and Russ and Valderrama (2012) have explored to what extent corporate bonds and bank loans play a different role in the financing of industrial corporations, given the different institutional framework of the two markets. The empirical analysis of the substitution between loans and corporate bonds has focused on the impact of monetary policy. Kashyap et al. (1993) and Kashyap et al. (1994), in particular, studying aggregate variables, find that the substitution is rather limited, and thus provide evidence supporting the hypothesis that banks may play a relevant role in the transmission of the monetary policy. More recently, Lemmon and Roberts (2010) make use of firm-level data to analyze the impact of supply-side shocks on the availability of credit to industrial firms. They find that shocks that hit the corporate bond market are imperfectly accommodated, so that they influence leverage ratios and investment decisions. Casalin and Dia (2014) study aggregate variables, finding that financial frictions are significant also when analyzing large aggregates, and that while external finance flows are driven by the gap between internally generated funds and investment needs, aggregate investment is only marginally constrained by the availability of external finance.

The impact of uncertainty on the real economy has been the subject of re-

newed attention in recent years. A large body of literature, starting with Schwert (1989, 2002), has provided substantial evidence that market volatility is associated with declining stock market prices as well as recessions, as high volatility is largely explained by technological shocks. Campbell et al. (2001), in particular, suggest that volatility measures help forecast GDP growth. Another large strand of literature suggests that uncertainty has a direct impact on economic activity, as it increases the option value of postponing investment decisions (see Dixit and Pindyck (1994)). For instance, Bloom (2009) compares the effects of uncertainty and productivity shocks on aggregate investment and output, suggesting that the former generate a more long-lasting impact than the latter. More recently, Beetsma and Giuliodori (2012) have analyzed the effect of market volatility on aggregate consumption and investment, finding that the impact on real variables is significant.

A rich empirical literature has investigated the relationships between stock and bonds markets. Campbell and Ammer (1993) show that the markets for stocks and Treasury bonds are not strongly influenced by the real interest rate. Connolly et al. (2005) analyze the time variation in the long term correlation between stock and bond returns, finding that such correlation declines with higher uncertainty. Baele et al. (2010) have developed a dynamic factor model to explain the comovements of stock and bond returns, finding that macroeconomic factors are important determinants. They also find that the level of liquidity is one of the main drivers of the correlation dynamics. More recently, Baker and Wurgler (2012) suggest that albeit the correlation between stock and bond returns is unstable,

bonds co-move with a subset of stocks that has relatively low return volatility and large and stable dividends. Chordia et al. (2005) show that liquidity in stock and bond markets is not independent and it is influenced by the monetary policy, as measured by changes in net borrowed reserves. Similarly, Goyenko and Ukhov (2009) find that the spillovers of liquidity across the stock and Treasury bond markets are significant. Scruggs and Glabadanidis (2003) find that the conditional volatilities in bond and stock markets respond asymmetrically to bond and stock returns. Brenner et al. (2009) discuss the impact of unexpected macroeconomic news on the volatility and the covariance of the returns on stocks, Treasury and corporate bonds, finding that news have a significant impact on volatilities, which varies across asset classes.

III Dataset

The dataset gathers monthly aggregate data for the volumes of *C&I* loans at all commercial banks ($LOAN_t$), as well as of primary placements of bonds (BND_t) and stocks ($STCK_t$) of non-financial corporations for the US economy.¹ The values are deflated by using the CPI index with base year 1983. We use the volume of outstanding loans, rather than the flows of new issues, because the average maturity of this aggregate is short, and most of the issuance is renewed continuously. In fact, the average maturity for the period 1997 - 2012 was 1.25 years whereas for

¹The volumes of C&I loans represent 19% of total aggregate loans at the end of 2009.

corporate bonds was 10.6 years.² The amount of corporate bonds outstanding in the year 2011 was of 5,215 billions, equivalent to 2,317 billions in terms of 1983 US dollars, while the average amount of outstanding C&I loans was 560 billions, so the total amount of bonds outstanding in recent years is roughly four times as large. The average monthly volume of corporate bonds and stocks issued in the same period was 16 and 7.1 billions. When the same volumes are aggregated over a time horizon of 15 months (corresponding to the average maturity of *C&I* loans) they sum to 240 billions for bonds and 106 for stocks, whereas the value of loans outstanding is equal to 577 billions. Thus, over this period the volume of new resources raised in financial markets were little more than one half of the amount granted by the banking system. Figure 1 displays the average volumes of outstanding C&I loans together with the issuance of corporate bonds and stocks re-scaled by a factor equal to the average maturity of the loans. In the initial part of the sample spanning from 1970 to 1997, the average amount of loans outstanding was 401 billions of 1983 dollars, whereas the average volumes of bonds and stock issued on a monthly basis were, respectively, 5.7 and 3.1 billions. Consequently, the share of market finance has grown substantially in the second part of the sample, and the issuance of corporate bonds has grown more than that of stocks.

FIGURE 1 HERE

²Data on the maturity of loans and corporate bonds are provided by the FED and Securities Industry and Financial Markets Association.

Our dataset includes also series for the returns on S&P500 and Barclays Corporate Bonds Index (BCBI), the yield spread between ten-year government bonds and three-month T-Bills, as well as an indicator of the size of the loan market computed as the ratio between the total volume of commercial and non commercial loans and nominal GDP. The period under analysis spans from January 1970 to October 2012 for all the series.³

We investigate the integration properties of the series $LOAN_t$, BND_t and $STCK_t$ by using a battery of unit root tests which includes standard ADF tests, DF-GLS de-trended, the Point Optimal and modified versions of the Sargan-Barghava and Phillips-Perron statistics.⁴ The empirical results reported in Table 1 show that none of the above tests reject the null at standard significance levels, while the same tests applied to series in first differences indicate stationarity, so that the three series under scrutiny are processes integrated of order one.⁵

Table 2 reports some descriptive statistics for the three series in first differences. The Ljung-Box Q statistics applied to raw series suggest the presence of strong serial correlation in all the three aggregates. When applied to detect serial correlation in squared series, the same statistics consistently reject the null, suggesting the presence of nonlinear dependence, possibly due to changing conditional volatility. The Ljung-Box Q statistics for leads and lags of raw and squared series

³Data are obtained from the Federal Reserve Bulletin, Federal Reserve Bank of St Louis, OECD, and Datastream.

⁴All of our specifications include a constant and a time trend in order to allow for trend stationarity in the series.

⁵The same unit root tests applied to the other series of our dataset soundly reject the null of non stationarity. The only exception is the size of loan market which is $I(1)$. As such, the series will be considered in first difference in the remaining part of the empirical analysis.

indicate the presence of strong interactions among the first and second moments of the series.⁶ As we would expect, the volumes of shares issued are more volatile than those of bonds, while the issuance of C&I loans is far less volatile.

TABLES 1 AND 2 HERE

We proceed by testing for the presence of co-integrating relationships among the series under scrutiny. Table 3 reports the results of the five different co-integration tests we consider. Both the Trace and Eigenvalue statistics indicate the existence of one co-integrating relationship at conventional significance levels. We then obtain very similar results when we apply the Johansen and Nielsen (2000) statistic which is consistent to the presence of structural breaks. The presence of one co-integrating relationship is also supported by the Phillips-Ouliaris, Engle-Granger and Gregory-Hansen residual-based tests which consistently reject the null of no co-integration at the 5% level. All in all, the above statistics provide convincing evidence that the three series are co-integrated.

TABLE 3 HERE

IV Methodology

The three series are modeled by means of a VECM in which the changes in the three aggregates depend on a constant μ_i , on their own P_i lags and cross lags, on the co-integrating relationship and on the disturbance terms ε_t^i that capture

⁶These last results are not reported to save space but are available from the authors.

the "unexpected shocks" on the dependent variables (for $i=1,2$ and 3). Thus, by assuming that the mean equations follow a VECM(p) stochastic process, each equation is specified as follows:

$$\begin{aligned} \Delta LOAN_t = \mu_1 + \sum_{p=1}^{P_1} \gamma_{11,p} \cdot \Delta LOAN_{t-p} + \sum_{p=1}^{P_2} \gamma_{21,p} \cdot \Delta BND_{t-p} + \\ + \sum_{p=1}^{P_3} \gamma_{31,p} \cdot \Delta STCK_{t-p} + \alpha_L \cdot z_{t-1} + \varepsilon_{1,t} \end{aligned} \quad (1)$$

$$\begin{aligned} \Delta BND_t = \mu_2 + \sum_{p=1}^{P_1} \gamma_{21,p} \cdot \Delta LOAN_{t-p} + \sum_{p=1}^{P_2} \gamma_{22,p} \cdot \Delta BND_{t-p} + \\ + \sum_{p=1}^{P_3} \gamma_{32,p} \cdot \Delta STCK_{t-p} + \alpha_B \cdot z_{t-1} + \varepsilon_{2,t} \end{aligned} \quad (2)$$

$$\begin{aligned} \Delta STCK_t = \mu_3 + \sum_{p=1}^{P_1} \gamma_{31,p} \cdot \Delta LOAN_{t-p} + \sum_{p=1}^{P_2} \gamma_{32,p} \cdot \Delta BND_{t-p} + \\ + \sum_{p=1}^{P_3} \gamma_{33,p} \cdot \Delta STCK_{t-p} + \alpha_S \cdot z_{t-1} + \varepsilon_{3,t}, \end{aligned} \quad (3)$$

where the coefficients α_L , α_B and α_S are the speed of adjustment to the long-run co-integrating relationship $z_{t-1} = LOAN_{t-1} - \beta_0 - \beta_1 BND_{t-1} - \beta_2 STCK_{t-1}$.⁷

Given the residuals $\varepsilon_{i,t}$, we model the conditional covariance matrix Σ_t of

⁷The subscripts 1, 2 and 3 correspond to the series $LOAN_t$, BND_t and $STCK_t$. The same notation is used throughout the remainder of the paper.

Eq.(4) by means of Asymmetric Diagonal VECH (Asy Diag VECH henceforth), BEKK and DCC GARCH specifications, where Ω_{t-1} is the information set at time $(t-1)$ (see Engle and Kroner (1995) and Engle (2002)).

$$\varepsilon_t = \begin{pmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \\ \varepsilon_{3,t} \end{pmatrix} \mid \Omega_{t-1} \sim N(0, \Sigma_t) \quad (4)$$

We supplement both the Asy Diag VECH and DCC specifications with additional terms to account for asymmetric effects in the conditional variances by using a multivariate version of the model proposed by Glosten et al. (1993).⁸

The Asy Diag VECH model is specified as follows:

$$\Sigma_t = \mathbf{C}_1 + \mathbf{G}_1 \odot \Sigma_{t-1} + \mathbf{A}_1 \odot \varepsilon_{t-1} \varepsilon_{t-1}' + \Gamma_1 \odot (\varepsilon_{t-1}^- \varepsilon_{t-1}^{-'}) \quad (5)$$

where \mathbf{C}_1 , \mathbf{G}_1 , \mathbf{A}_1 , Γ_1 and $\varepsilon_{t-1}^- = [I(\varepsilon_{1,t-1} < 0)\varepsilon_{1,t-1}, \dots, I(\varepsilon_{3,t-1} < 0)\varepsilon_{3,t-1}]$ are all (3×3) parameter matrices.⁹ The asymmetric volatility coefficients can be found in the matrix Γ_1 and they should be positive, suggesting that the volatility tends to rise (fall) when the previous innovation is negative (positive). To reduce the parameters under estimation we decide to model asymmetric effects only in the conditional variances by setting the off-diagonal elements of Γ_1 to zero so that the

⁸The asymmetric volatility phenomenon is a common feature of secondary stock and bond markets, where bad news generate larger volatility than good news. Since primary placements of stocks and bonds are largely driven by prices on secondary markets, the former should inherit statistical features of the latter such as the so-called leverage effect.

⁹ \odot denotes the Hadamard product (element by element matrix multiplication) and $I(\varepsilon_{i,t-1} < 0)$ is an indicator variable which takes value 1 if $\varepsilon_{i,t-1} < 0$, and zero otherwise for $i=1,2,3$.

model consists of a total of 21 parameters.

The second class of volatility models we consider is the BEKK GARCH which enables the implementation of formal tests for the presence of volatility spill-over among the markets under scrutiny. The parametrization for a GARCH(1,1) is specified as follows:

$$\Sigma_t = \mathbf{C}_2' \mathbf{C}_2 + \mathbf{G}_2' \Sigma_{t-1} \mathbf{G}_2 + \mathbf{A}_2' \varepsilon_{t-1} \varepsilon_{t-1}' \mathbf{A}_2 \quad (6)$$

where \mathbf{G}_2 , \mathbf{A}_2 and \mathbf{C}_2 are (3×3) matrices with this last restricted to be upper triangular.¹⁰

The conditional correlation matrix for the DCC specification is obtained as by-product of the matrix \mathbf{Q}_t of dimension (3×3) , which is specified as a function of the standardized residuals $\tilde{\varepsilon}_{t-1}$, the unconditional covariance matrix of these last (denoted as $\overline{\mathbf{Q}}$), and two unknown scalar parameters a and b :

$$\mathbf{Q}_t = (1 - a - b) \overline{\mathbf{Q}} + a \tilde{\varepsilon}_{t-1} \tilde{\varepsilon}_{t-1}' + b \mathbf{Q}_{t-1} \quad (7)$$

The DCC-based conditional correlations are computed by first estimating the individual univariate GARCH processes to recover the standardized residuals $\tilde{\varepsilon}_{t-1}$ and then the parameters a and b from eq.(7).¹¹ Thus, the DCC covariance matrix is obtained by estimating only 2 parameters against the 21 and 25 involved in

¹⁰Given the heavy parametrization which involves as many as 25 parameters, we decide not to model the asymmetric effects on the volatility of the three markets.

¹¹Also in this case, the conditional variances are specified by following Glosten et al. (1993).

the Asy Diag VECM and BEKK previously set out.¹² The VECM and GARCH specifications are estimated by following the two-step approach suggested by Lin et al. (1994).¹³

The final part of the empirical analysis involves the identification of macroeconomic factors that could explain the time-varying nature of the co-movements among the three markets, adapting models developed to investigate the levels of co-movement between secondary stock and bond market prices (see, e.g., Connolly et al. (2007) and Wang and Moore (2008)). We investigate this issue by regressing time-varying correlation coefficients against business cycle and monetary policy indicators, as well as returns on stock and bond markets. More specifically, we estimate the following linear regressions (for $i, j=1, 2, 3$ and $i \neq j$):

$$\begin{aligned} \rho_{ij,t} = & a_0 + \sum_{l=1}^L a_l \rho_{ij,t-l} + b_1 R_{BCBI,t} + b_2 R_{S\&P,t} + b_3 \Delta LM_t + b_4 YD_t + \\ & + b_5 \sigma_{BCBI,t} + b_6 \sigma_{S\&P,t} + \sum_{k=1}^3 c_k DUM_{i,t} + \varepsilon_{ij,t}, \end{aligned} \quad (8)$$

where $\rho_{ij,t-l}$ is the lagged correlation coefficient, $R_{BCBI,t}$ and $R_{S\&P,t}$ are the returns on bond and stock indices, LM_t is the ratio of total loans to GDP which is commonly used to capture the banking sector development, YD_t is the yield spread between ten-year and three-month interest rates, and $\sigma_{BCBI,t}$ and $\sigma_{S\&P,t}$ are

¹²Maximum likelihood estimates of the above GARCH specifications are obtained by using the Broyden-Fletcher-Goldfarb-Shanno (BFGS) algorithm in RATS.

¹³These authors show that their two-step approach is asymptotically equivalent to a joint estimation of the two models, as the least squares estimator used in the VECM is still unbiased and consistent in presence of heteroscedasticity.

the volatility indicators for the secondary markets.¹⁴ Moreover, in order to analyze the impact of a number of major events on the level of co-movement between the three aggregates, we consider several dummy variables that capture episodes such as the stock market crash of October 1987 ($DUM_{1,t}$), the outbreaks of the Subprime Crisis in September 2008 ($DUM_{2,t}$) and the financial turmoil which followed the fiscal showdown of June 2011 ($DUM_{3,t}$).¹⁵ Empirical estimates of Eq.(8) are carried out by means of Seemingly Unrelated Regressions (SUR) in order to exploit the potential contemporaneous correlation among the disturbance terms. The same regressions are then re-estimated in a time-varying parameter setting by means of Kalman filter.

We carry out the above exercise by using the conditional correlations obtained from the Asy Diag VECH specification. This choice is motivated by the large number of parameters as well as the ability to account for asymmetric effects, which make the Asy Diag VECH specification well suited to deliver more fine-tuned conditional correlations than the BEKK and DCC. We instead make use of the BEKK specification to shed light on the transmission of volatility among the markets under scrutiny, and we employ the DCC model to check the robustness of our empirical estimates. Empirical results set out in the next section suggest that the above GARCH specifications produce conditional covariance matrices with

¹⁴Following Syllignakis and Kouretas (2011) we model $\sigma_{BCBI,t}$ and $\sigma_{S\&P,t}$ as conditional standard deviations obtained by fitting AR-GARCH(1,1) specifications to both BCBI and S&P500 returns.

¹⁵September 2008 corresponds to two key episodes which have characterized the recent Subprime crisis: the nationalization of Fannie Mae and Freddy Mac, and the filing for bankruptcy of Lehman Brothers. The fiscal showdown of the summer of 2011 corresponds to a period of severe tensions in the US bond market.

similar features, and that the Asy Diag VECM yields a better fit of the data than the BEKK.

V Empirical Results

V.1 Co-integration and Volatility

Empirical estimates of the co-integrating relationship z_{t-1} , of the parameters α_L , α_B and α_S which govern the adjustments to the long-run equilibrium, as well as some diagnostic statistics for the estimated VECM are reported in Table 4. The coefficient estimates of the co-integrating relationship are very similar to each others and show that there is a positive long-run linkage among the three aggregates.¹⁶ For instance, D-OLS estimates suggest that, other things being equal, a 1% increase in the issuance of corporate bonds and stocks is associated, respectively, with a 0.19% and 0.11% increase in the volume of outstanding loans.¹⁷

The speed of adjustment α_L and α_B are statistically significant and show opposite sign, whereas α_S is not significant at standard significance levels. Thus, $STCK_t$ is weakly exogenous and, when deviations from the long-run equilibrium occur, the equilibrium is restored through adjustments of both $LOAN_t$ and BND_t .

Finally, we analyzed the stability of the cointegration relationships reported in Table 3 by using the SupF, MeanF and Lc stability tests proposed by Hansen (1992). These statistics soundly reject the null of stability at the 1% level sug-

¹⁶The large magnitude of the constant terms capture the larger scale of the series $LOAN_t$ in comparison to the regressors.

¹⁷We obtain similar results for FM-OLS, C-OLS and JOH-ML estimates.

gesting that, over the sample period under scrutiny, the coefficients of the co-integrating relationship are time varying. Given the instability in the parameters, we check whether the evidence of one co-integrating relationship survives when tested on the subperiods 1970:01-1979:12, 1980:01-1989:12 and 1990:01-2012:10. Co-integration tests consistently suggest that the above subsamples are characterized by the presence of one co-integrating relationship. We then estimate such relationship over the three subperiods and we find that the results set out in Table 3 are mainly driven by the last 20 years of the sample.¹⁸

TABLE 4 HERE

*We then use the residuals generated by the VECM to estimate the Asy Diag VECM, DCC and BEKK specifications previously set out.*¹⁹ Empirical results for the Asy Diag VECM specification are reported in first three columns of Table 5.²⁰ Statistical tests for the null of constant covariance matrix Σ_t are soundly rejected at standard significance levels.²¹ When we compare the conditional volatilities of the different aggregates, past shocks seem to exert a stronger impact on $LOAN_t$

¹⁸The empirical results for the stability tests and the three subsamples are not reported but are available from the authors upon request.

¹⁹Empirical estimates of the DCC specification are carried out by initially fitting univariate volatility models to the three series under scrutiny in order to compute standardized residuals. The conditional covariance matrix of Eq.(7) is then estimated over the sample of standardized residuals to obtain values of the parameters a and b .

²⁰The stationary conditions for the covariance matrix Σ_t are fulfilled as the largest eigenvalue of the matrix $\mathbf{A}_1 + \mathbf{G}_1 + \Gamma_1$ is 0.997. Moreover, the sufficient conditions to ensure positive definiteness of Σ_t hold as the individual matrices \mathbf{A}_1 , \mathbf{G}_1 and Γ_1 are semi definite and \mathbf{C}_1 is positive definite.

²¹The LR statistic for the null $H_0 : a_{1,11} = a_{1,12} = a_{1,13} = a_{1,23} = a_{1,33} = g_{1,11} = g_{1,12} = g_{1,13} = g_{1,23} = g_{1,33} = 0$ calculates to 4973.3, and with the degrees of freedom being equal to 10, the null is rejected at standard significance levels. Similarly, the null that all the ARCH elements in \mathbf{A}_1 or the GARCH elements in \mathbf{G}_1 are equal to zero is also soundly rejected.

than they do on BND_t and $STCK_t$. Past volatilities, on the other hand, are the main driver for current volatilities of both BND_t and $STCK_t$. Moreover, the null of absence of asymmetric effects is also rejected at standard significance levels.²² The asymmetric volatility parameter for the bond market is positive and significant, supporting the notion that previous bad news (represented by negative innovations) increase the volatility of bond issuance more than good news. This result is in line with the evidence obtained by Brenner et al. (2009), who find that the arrivals of bad news have a larger impact on the volatility of bond and stock returns than good news. Furthermore, corporate bond markets are subject to dramatic liquidity crunches in periods of financial distress, when several classes of securities becomes affected by the “Lemons” problem, as it was the case for corporate bonds issued by banks, and asset backed securities in the months following the collapse of Lehman Brothers.

Empirical estimates of the DCC specification are fairly similar to those obtained for the Asy Diag VEC model. The parameters governing the DCC matrix are both with the expected sign and magnitude and statistically significant at the 1% level.²³ The shocks to the conditional covariance matrix are persistent, with a half-life of more than 6 months.²⁴

²²The LR statistic for the null $H_0 : a_{2,11} = a_{2,22} = a_{2,33} = 0$ calculates to 7.030 with p-value equal to 0.709.

²³The conditions for stationarity and positivity of the conditional variances are satisfied as for each process the ARCH and GARCH parameters are positive and their sum plus half the value of the parameter capturing the asymmetric effects is lower than 1. Similarly, the stationarity and positivity conditions for the matrix \mathbf{Q}_t are satisfied as both the parameters a and b are positive and their sum lower than 1.

²⁴The half-life is computed as $\ln(0.5)/\ln(a^2 + b^2)$.

Empirical estimates of the processes governing the conditional variances of the BEKK specification are reported in the last three columns of Table 5.²⁵ Since the intercept terms as well as the coefficients attached to lagged variances, covariances and error terms consist of non-linear functions of the elementary parameters of the model, their statistical significance is evaluated by using the Delta method. Also in this case, asymptotic standard errors are generally small relative to the point estimates, suggesting that the parameters are precisely estimated and that the transmission of volatility across the three market is actually a feature of our data.²⁶ The diagnostic statistics reported in the bottom panels of Table 4 and 5 suggest that both the VECM and GARCH models are reasonably well specified as their residuals are characterized by negligible serial correlation.²⁷

In the remainder of the paper we make use of the conditional correlations computed from the Asy Diag VECM conditional covariance matrix. This specification, in fact, should produce more fine-tuned correlation indices as it is richer in parameters than the DCC and, unlike the BEKK specification, accounts for the presence of asymmetric effects. Moreover, both the Akaike and Schwarz criteria

²⁵To save space we do not report the parameter estimates which govern the conditional covariances between $LOAN_t$ and BND_t , $LOAN_t$ and $STCK_t$, and BND_t and $STCK_t$.

²⁶The stationarity condition for the BEKK covariance matrix Σ_t is satisfied as the sum the Kroneker products of the ARCH and GARCH terms has eigenvalues less than 1 in modulus.

²⁷The lower panel of Table 4 reports a battery of diagnostic tests for serial correlation and heteroscedasticity in the residuals of the VECM. Both the Ljung-Box and LM tests fail to reject the null of absence of serial correlation. The same Ljung-Box statistics reject the null when applied to squared residuals, suggesting the presence of heteroscedasticity. Similarly, ARCH LM tests reject the null of homoscedasticity suggesting the presence of ARCH effects in the residuals. The same statistics are reported in Table 5 for the Asy Diag VECM, DCC and BEKK specifications, highlighting absence of serial correlation and heteroscedasticity. Both the Sign Bias tests suggest moderate presence of asymmetry in the standardized residuals.

show lower values for the Asy Diag VECH model than the BEKK specification, suggesting that the former may be preferred to the latter. Empirical results show some consistency among the conditional covariance matrices obtained from the three specifications. Both the Asy Diag VECH and BEKK conditional standard deviations are characterized by very similar dynamics. When we compare the conditional correlations such degree of similarity tends to weaken, yet unconditional correlations carry the same sign and similar magnitudes. Similarly, the unconditional DCC covariances show the same sign as those obtained from Asy Diag VECH and BEKK specifications.

TABLE 5 HERE

Figures 2, 3 and 4 display the conditional correlation coefficients among the three markets. The conditional correlation between BND_t and $STCK_t$ is time varying and remains positive for the entire sample with a mean value of 0.53, indicating that factors different from relative returns play an important role in the determination of the equilibrium quantities, since returns are poorly correlated, as discussed by Campbell and Ammer (1993). The positive conditional correlation is in line with the findings of Goyenko and Ukhov (2009), suggesting that the liquidity of the stock and Treasury bond markets Granger-cause each other. This result is also in line with Casalin and Dia (2013) who find that debt and equity are complementary sources of finance in the United States. The positive correlation indicates that idiosyncratic shocks in the two markets are positively interrelated. Thus, industrial corporations can substitute bonds for shares and vice versa to

a limited extent only, as common factors influence the availability of external finance from the two classes of securities.

FIGURE 2 HERE

The conditional correlation between $LOAN_t$ and BND_t takes values consistently negative over time, with a mean of -0.12, so that the two aggregates are substitutes. This result is consistent with previous findings by Kashyap et al. (1993), Kashyap et al. (1994) and Lemmon and Roberts (2010), and it suggests that developed corporate bond markets are important for risk sharing, as financial flows from these last are larger when bank finance becomes scarcer, and vice versa. Although corporate bonds and loans are far from being perfect substitutes, the correlation is negative for almost the entire sample and persistent over time. The fact that the average correlation is strongly negative over the initial 15 years of the sample, and that it decreases in absolute value and remains substantially stable afterwards suggests that the development of financial markets as well as of banking regulation might have played an important role. More specifically, up until 1987 banks were subject to regulation Q, which forbade the payment of interest on bank deposits, so that their capability to grow by attracting deposits was severely constrained. As a result, market substitutes for deposits, such as money market mutual funds, developed quickly and market finance in general became more easily available to industrial firms. The birth of the high yield corporate bond market extended access of risky borrowers to market finance. Starting from values near to zero in the mid-70s, in 1984 the issuance of junk bonds reached a

peak of 24% of the total issuance of corporate bonds, whereas in recent years the average issuance has been as high as 25% of the total.²⁸ We thus put forward the hypothesis that during the early period of the sample the strongly negative correlation was driven by the incapability of the banking sector to satisfy the growing demand for finance from the industrial system, and the disintermediation process has progressively reduced the role of banks. In line with this interpretation, the phase-out of regulation Q in 1987 is a turning point, as in the late 1980s the negative correlation becomes far smaller in absolute terms and it tends to stabilize during the last 10 years of the sample.

FIGURE 3 HERE

The conditional correlation between $LOAN_t$ and $STCK_t$ takes values prevalently negative during the period 1970-1998, and it approaches values close to zero for the last 14 years of the sample.

FIGURE 4 HERE

V.2 Volatility Spill-overs across Primary Markets

We then use the BEKK parametrization of Eq.(6) to shed light on the transmission of volatility among the three sources of external finance. Empirical results suggest that there is strong spill-over volatility between the primary markets for bonds and stocks. The bond market receives volatility directly from, and transmits

²⁸See Taggart (1987) and Reilly et al. (2009).

volatility directly to the stock market through both the conditional variances and shocks, and a similar pattern occurs through both their past covariance $\sigma_{23,t-1}$ and cross-shocks $\varepsilon_{2,t-1}\varepsilon_{3,t-1}$.

The volatility spill-overs between the market for loans and those for shares and bonds are somewhat less strong. The loan market receives volatility only indirectly through $\sigma_{13,t-1}$ and $\varepsilon_{1,t-1}\varepsilon_{2,t-1}$, while it does not transmit volatility neither directly or indirectly to any of the other markets.

We double check the above results by carrying out standard Granger-causality tests, which impose zero constraints on the off-diagonal elements of the ARCH and GARCH matrices of Eq.(6). Also in this case, we find evidence of strong spill-over volatility between primary bond and stock markets. In fact, the null that the bond market does not transmit volatility to the stock market, and vice versa, are soundly rejected at standard significance levels. Similarly, the null that the bond and stock markets do not transmit volatility to the loan market are soundly rejected, whereas the null that the loan market does not transmit volatility to any of the other markets cannot be rejected at the 5% level.²⁹ All in all, the above results suggest that the volatilities in stock and bond markets are strongly interconnected. These markets, however, are relatively insulated from outside shocks deriving from the loan market, and vice versa.

²⁹Empirical results are not reported to save space, but are available from the authors upon request.

V.3 Co-movement among Primary Markets

SUR estimates of Eq.(8) are reported in Table 6.³⁰ The magnitude of the auto-regressive terms suggests that the impact of external shocks on the contemporaneous correlations is fairly persistent, but the memory of the shocks is not extremely long. Moreover, they provide empirical support for the hypothesis of time variability in all the correlation coefficients under scrutiny. The explanatory power of the regressions is fairly high as the R-squared range from 0.504 to 0.871.³¹ Thus, macroeconomic factors explain a sizable share of the variability in the above correlation coefficients. As Goyenko and Ukhov (2009) find that illiquidity is also explained by macroeconomic factors, we now try to disentangle the impact of fundamental macroeconomic variables from that of financial variables capturing short-term market trends, or expectations of future values.

V.3.1 Bonds and Stocks

The correlation between bonds and stocks is significantly influenced by financial variables and it is strongly pro-cyclical, as all the statistically significant regressors are leading indicators of the business cycle. More specifically, the yield spread, positive and significant at the 1% level, is the indicator which exerts the strongest impact. As positive shocks to the yield spread are associated with expectations of economic expansion and/or rising inflation, the correlation increases when financial markets anticipate growth of nominal GDP. Similarly,

³⁰The optimal number of lags L for all the three regressions under analysis is equal to 1.

³¹The large explanatory power is not the result of spurious regression as standard Augmented Dickey-Fuller tests applied to the residuals soundly reject the null of unit root.

positive stock market shocks yield a positive impact on the correlation, confirming that the link is weaker when expectations of a slowdown generate a reduction of stock prices, followed by a decline of share issuance.

Financial shocks, associated with spikes in stock market volatility, are followed by significantly lower levels of correlation between the markets of shares and bonds, so that the relationship of complementarity weakens.³² Since stock market volatility is associated with lower stock prices, during periods of high volatility the issuance of shares dries up; the issuance of corporate bonds is similarly reduced in periods of financial distress, but to a much lesser extent than that of stocks, so that the correlation declines substantially.³³

Among the episodes which have characterized the recent US economic history, the 1987 stock market crash, the 2008 Subprime Crisis and the 2011 fiscal showdown exert a statistically significant impact on the levels of co-movement between the two primary markets. They are, in fact, associated with a substantial reduction in the levels of co-movement between primary stock and bond markets. All in all, the correlation between the two aggregates is pro-cyclical, equity and bonds are strongly complementary sources of finance. However, the link between the two markets becomes less tight when financial markets expect a recession, or when negative shocks hit the economy.

FIGURE 5 HERE

³²These results are in line with Connolly et al. (2007) and Brenner et al. (2009) who showed that the correlation of returns across bond and stock markets decreases when market volatility heightens or “bad” news are announced.

³³Volatility in itself does not significantly influence the aggregate issuance of shares, as discussed by Casalin and Dia (2009).

We then re-estimate Eq.(8) in a time-varying parameters setting. Figure 5 displays the coefficients of the variables whose shocks generate a significant impact on the correlation coefficient. Both $R_{S\&P,t}$ and YD_t exert a positive and significant impact on the levels of co-movement during the second half of the period only. On the contrary, the negative impact of $\sigma_{S\&P,t}$ remains strongly significant for the entire sample period.

V.3.2 C&I loans and Bonds

The correlation between loans and bonds responds positively to innovations in the yield spread, significant at the 1% level, suggesting that the negative correlation becomes smaller in absolute value with expectations of rising nominal GDP.

Financial shocks influence the correlation through the impact on bond markets. The volatility of corporate bond prices, in fact, generates a strongly significant negative impact on the correlation, reinforcing the relationship of substitutability between $LOAN_t$ and BND_t .

Higher levels of the ratio between bank credit and GDP, as captured by the regressor ΔLM_t , exert a positive and strongly significant impact on the correlation coefficient, so that the negative link between the two aggregates is weakened. Thus, the two markets become less negatively correlated when credit expansion grows faster than GDP, while in periods of credit contraction the two markets diverge more significantly. Since aggregate credit is highly pro-cyclical, this result confirms that for US firms it becomes easier to substitute bonds for loans during

the recessionary phase of the cycle. Moreover, this result provides strong support for our hypothesis that the strong negative correlation of the initial years of the sample is at least in part explained by the regulatory constraints imposed on the banking industry, and it has declined as the progressive deregulation of the banking industry, begun in the late 1980s, has enabled banks to compete in corporate finance. The analysis of the dummy indicators suggests that only the fiscal showdown of the summer 2011 has a significant impact on the correlation, whereas the other exogenous shocks are not statistically significant.

Figure 6 displays the values of the statistically significant coefficients when Eq.(8) is estimated in a time-varying parameter setting. The impact of ΔLM_t and $\sigma_{BCBI,t}$ remains statistically significant over the entire sample period, whereas the yield spread exerts a positive and significant impact on the level of correlation only for the second half of the sample.

FIGURE 6 HERE

V.3.3 C&I loans and Stocks

The behaviour of the conditional correlation between loans and stocks is fairly similar to that between loans and bonds, further confirming that the cyclical factors driving bond and stock primary markets are analogous. The correlation coefficient responds positively to innovations in the yield spread, and negatively to the volatility of corporate bonds. Moreover, the coefficient measuring the change in the ratio between bank credit and GDP is positive and significant, suggesting that higher levels of this last weaken the negative correlation. The symmetry of

this result with that found for the loan and bond markets suggests that changes in the regulation of the banking industry is an important driver of the co-movement between loan, bond and stock markets, whereas specific innovations in securities markets as the development of the market for junk bonds seem to play a less relevant role. Once again, the correlation is strongly pro-cyclical, and it tends to decline following financial shocks.

Both the 1987 Crash and September 2008 shock strengthen the negative co-movement between the two markets. The 2011 fiscal showdown seems instead to exert an opposite impact as, other things being equal, it pushes the correlation coefficient towards positive values.

FIGURE 7 HERE

The time-varying coefficients displayed in Figure 7 show that the impact of both ΔLM_t and $\sigma_{BCBI,t}$ remains statistically significant over the entire sample period, whereas the yield spread exerts a positive and significant impact on the levels of correlation only for the last decade of the sample.

TABLE 6 HERE

VI Conclusions

This study sheds light on the linkage among the equilibrium aggregate volumes of bank finance, and the issuance of corporate bonds and stocks over the period from 1970 to 2012. Our empirical results suggest that the three aggregates

share a common stochastic trend as the variables are co-integrated. We then focus on the second moments of the series, studying in particular their conditional correlations over several business cycles. We find that the three classes of securities are interrelated, their levels of co-movement vary over time, and financial variables explain sizeable proportions of such variability. *We also find strong spill-over volatility between the primary markets for bonds and stocks, while the volatility spill-overs among these last and the market for loans are less strong. Thus, bond and stock markets are relatively insulated from outside shocks deriving from the loan market, and vice versa.*

The correlation between primary markets for bonds and stocks is always positive, and remarkably high over the entire sample, although it tends to decline in periods of recession and financial distress. Both these markets are instead negatively correlated with the loan market, suggesting that bank loans and market sources of finance are substitutes. More specifically, the conditional correlation between primary placements of corporate bonds and C&I loans assumes negative values over most of the sample under scrutiny. Thus, the development of efficient bond markets is a fundamental tool to increase the resilience of the economy, in particular when negative shocks affect both industrial corporations and the banking industry.

The co-movements of corporate bonds and stocks issued with C&I loans are explained by financial variables such as the yield spread, the volatility of stock and bond market prices as well as the size of bank credit to GDP. All these variables exert a strong impact on the two correlation coefficients, so that when financial

markets expect a recession, when they are highly volatile or when bank lending declines, the already negative correlations exacerbate, and it becomes easier to substitute bank finance for financial market sources, and vice versa.

Finally, macroeconomic and financial shocks such as the occurrence of the 1987 stock market crash, the Subprime crisis, or the tensions in bond markets following the fiscal showdown of the summer 2011 consistently weaken the levels of co-movement between primary financial markets.

Overall these results suggests that the impact of exogenous shocks on real variables is mitigated by the availability of different sources of finance that become less interdependent in periods of economic downturn or financial distress.

Table 1: Unit root tests for the series $LOAN_t$, BND_t and $STCK_t$.

	ADF^b	$DF-GLS^c$	MZ_{α}^d	MZ_t^{\dagger}	MSB^{\ddagger}	MPT_{α}^{\S}	ERS_{α}^{\P}
$LOAN_t$	-2.537	-2.504	-12.61	-2.511	0.199	7.222	7.201
BND_t	-3.299	-2.416	-9.42	-2.107	0.223	9.943	10.044
$STCK_t$	-2.480	-2.520	-8.930	-2.098	0.234	10.260	10.221

Notes: Sample period 1970:01 - 2012:10. Unit-root tests applied to series in levels. * (**) statistically significant at 5 (1%) level. ^b Augmented Dickey-Fuller test with critical values at 5 (1%) level equal to -3.418 (-3.976). ^c Dickey-Fuller GLS detrended test with critical values at 5 (1%) level equal to -2.890 (-3.480). ^d Ng and Perron's (2001) Modified Phillips-Perron statistic with critical values at 5 (1%) level equal to -17.3 (-23.8). [†] Modified Phillips-Perron statistic with critical values at 5 (1%) level equal to -2.910 (-3.420). [‡] Modified Sargan-Barghava test with critical values at 5 (1%) level equal to 0.168 (0.163). [§] Elliott et al (1996) Optimal Point statistic with critical values at 5 (1%) level equal to 5.620 (3.960). [§] Modified Optimal Point statistic with critical values at 5 (1%) level equal to 5.480 (4.030). Tests computed using spectral GLS de-trended AR kernel based on Modified SIC.

Table 2: Summary statistics for the series $LOAN_t$, BND_t and $STCK_t$ taken in first difference.

	$LOAN_t$	BND_t	$STCK_t$
Mean	7.462	0.385	0.149
Std Dev	33.92	39.57	19.43
Skew	0.072 (0.536)	0.249 (0.032)	-0.448 (0.000)
Kurt	0.391 (0.093)	4.671 (0.000)	3.532 (0.000)
Obs	513	513	513
Q(4)	455.3 (0.000)	69.79 (0.000)	67.10 (0.000)
Q(8)	738.0 (0.000)	84.38 (0.000)	69.16 (0.000)
Q²(4)	40.60 (0.000)	156.2 (0.000)	161.5 (0.000)
Q²(8)	56.88 (0.000)	222.2 (0.000)	303.6 (0.000)

Notes: Sample period 1970:01 - 2012:10. Statistics applied to series in first differences. Skew and Kurt are statistical tests for the null of skewness equal to 3 and kurtosis equal to 0. Q(n) and Q²(n) are Ljung-Box statistic for serial correlation in raw and squared series up to lag n. P-values in parentheses.

Table 3: Co-integration tests for the series $LOAN_t$, BND_t and $STCK_t$.

No. Co-integrating Relationships	Trace ^b ₁	EIGEN ^b	Trace [§] ₂			
0	57.61**	33.12**	38.86**			
1	24.49	14.45	8.154			
2	10.04	10.04	0.733			
	EG-Z _α [‡]	EG-Z _t [‡]	PO-Z _α [†]	PO-Z _t [†]	GH-Z _α [‡]	GH-Z _t [‡]
1	-30.35*	-3.864*	-133.4**	-8.667**	-69.65**	-6.45**

Notes: Sample period 1970:01 - 2012:10. * (**) statistically significant at 5 (1%) level. ^b Trace and Max Eigenvalues statistics with critical values at 5% level equal to 42.44 and 25.54 for zero co-integrating relationship, 25.32 and 18.96 for one and 12.25 for two. [§] Johansen and Nielsen (2000) Trace statistic with simulated critical values at 10 (5%) level equal to 38.2 (41.3) for zero co-integrating relationship, 22.0 (24.5) for one and 9.9 (11.7) for two (see Table 1 in Giles and Godwin (2012)). [†] Phillips-Ouliaris (1990) residuals-based tests for the null of no co-integration with critical values at 5% level equal to -26.94 and -3.767. [‡] Engle-Granger residuals-based tests for the null of no co-integration with critical values at 5% level equal to -26.94 and -3.767. [‡] Gregory-Hansen (1996) residuals-based tests for the null of no co-integration with critical values at 5% level equal to -46.98 and -4.92.

Table 4: D-OLS, FM-OLS, C-OLS and JOH-ML estimates of co-integrating relationship among $LOAN_t$, BND_t and $STCK_t$.

	β_0	β_1	β_2	α_L	α_B	α_S
D-OLS [§]	3250*** (130.8)	9.219*** (1.495)	11.54*** (2.109)			
FM-OLS [†]	3172*** (220.8)	9.983*** (2.031)	11.56*** (3.884)			
C-OLS [‡]	3157*** (223.8)	10.23*** (2.282)	11.38** (4.374)			
JOH-ML	3002.2 (3.099)	9.841*** (3.099)	4.025 (4.388)	-0.012*** (0.003)	0.015*** (0.004)	-0.003 (0.002)
Q(6)				0.664 (0.990)	0.547 (0.995)	0.571 (0.993)
Q(12)				2.608 (0.990)	2.166 (0.990)	4.843 (0.960)
LM(4) [‡]					12.84 (0.170)	
LM(8) [‡]					15.78 (0.070)	
Q ² (6)				30.76 (0.000)	102.4 (0.000)	76.31 (0.000)
Q ² (12)				33.91 (0.000)	193.3 (0.000)	209.4 (0.000)
ARCH(4) [§]				29.1 (0.000)	47.8 (0.000)	34.9 (0.000)
R ²				0.601	0.504	0.510

Notes: Sample period 1970:01 - 2012:10. Estimated co-integrating relationship is $LOAN_t = \beta_0 + \beta_1 BND_t + \beta_2 STCK_t$. Parameters α_L , α_B and α_S are speed of adjustment. Standard deviations in parentheses. * (**) [***] statistically significant at 10% (5%) [1%] level. [§] Stock and Watson's (1993) Dynamic OLS estimated with 2 lead/lag and HAC robust standard errors. [†] Phillips and Hansen's (1990) Fully Modified OLS. [‡] Park's (1992) Canonical OLS. Bartlett kernel and Andrews (1991) bandwidth selector used to compute both FM-OLS and C-OLS estimates. Q(n) and Q²(n) are Ljung-Box statistics for serial correlation up to lag n in raw and squared raw residuals in any of the VECM equations. [‡] LM test for serial correlation in raw residuals up to lag 4 and 8. [§] ARCH LM test for heteroscedasticity in residuals up to lag 4. P-values in parentheses. Adjusted R² calculated as $1 - (1 - R^2)/(T - 1/T - k)$.

Table 5: Maximum Likelihood Estimates of Asy Diag VEC, DCC and BEKK models.

	Asy Diag VEC			DCC			BEKK	
	LOAN _{<i>t</i>}	BND _{<i>t</i>}	STCK _{<i>t</i>}	LOAN _{<i>t</i>}	BND _{<i>t</i>}	STCK _{<i>t</i>}	LOAN _{<i>t</i>}	STCK _{<i>t</i>}
const ₁	1×10 ^{-4*} (6×10 ⁻⁵)	-	-	1×10 ^{-4*} (6×10 ⁻⁵)	-	-	2×10 ^{-9***} (2×10 ⁻¹⁴)	-
const ₂₁	-1×10 ⁻⁵ (1×10 ⁻⁵)	-	-	-0.010*** (0.002)	-	-	-	-
const ₃₁	-2×10 ⁻⁵ (2×10 ⁻⁵)	-	-	-0.011*** (0.002)	-	-	-	-
const ₂	-	4×10 ⁻⁶ (3×10 ⁻⁶)	-	-	7×10 ^{-6*} (4×10 ⁻⁶)	-	4×10 ⁻⁸ (4×10 ⁻⁶)	-
const ₃₂	-	2×10 ⁻⁶ (2×10 ⁻⁶)	-	-	0.116*** (0.019)	-	-	-
const ₃	-	-	5×10 ^{-6**} (2×10 ⁻⁶)	-	-	7×10 ^{-6***} (2×10 ⁻⁶)	-	4×10 ⁻⁴ (0.000)
σ _{1,t-1} ²	0.579*** (0.151)	-	-	0.573*** (0.161)	-	-	0.405*** (0.089)	0.008 (0.007)
σ _{21,t-1} ²	0.765*** (0.163)	-	-	-	-	-	0.094 (0.079)	-0.042** (0.021)
σ _{31,t-1} ²	0.391 (0.582)	-	-	-	-	-	0.096** (0.043)	0.022** (0.011)
σ _{2,t-1} ²	-	0.906*** (0.018)	-	-	0.902*** (0.021)	-	0.005 (0.009)	0.054*** (0.018)
σ _{32,t-1} ²	-	0.905*** (0.068)	-	-	-	-	0.011 (0.012)	-0.058*** (0.011)
σ _{3,t-1} ²	-	-	0.877*** (0.021)	-	-	0.807*** (0.023)	0.006 (0.005)	0.015** (0.007)
ε _{1,t-1} ²	0.278*** (0.083)	-	-	0.279*** (0.084)	-	-	0.132* (0.077)	4×10 ⁻⁴ (0.002)
ε _{2,t-1} ε _{1,t-1}	0.036 (0.031)	-	-	-	-	-	-0.151* (0.082)	0.036 (0.105)
ε _{3,t-1} ε _{1,t-1}	0.036 (0.058)	-	-	-	-	-	-0.052 (0.046)	0.013 (0.040)
ε _{2,t-1} ²	-	0.074*** (0.018)	-	-	0.078*** (0.021)	-	0.043 (0.037)	0.790*** (0.052)
ε _{3,t-1} ε _{2,t-1}	-	0.052* (0.031)	-	-	-	-	0.030 (0.031)	0.606*** (0.038)
ε _{3,t-1} ²	-	-	0.103*** (0.021)	-	-	0.109*** (0.024)	0.005 (0.008)	0.116*** (0.011)
ε _{1,t-1} ² I(ε _{1,t-1} < 0)	0.080 (0.201)	-	-	0.082 (0.208)	-	-	-	-
ε _{2,t-1} ² I(ε _{2,t-1} < 0)	-	0.039** (0.015)	-	-	0.031** (0.016)	-	-	-
ε _{3,t-1} ³ I(ε _{3,t-1} < 0)	-	-	0.007 (0.018)	-	-	6.0×10 ⁻⁴ (0.018)	-	-
a	-	-	-	-	0.143*** (0.022)	-	-	-
b	-	-	-	-	0.757*** (0.036)	-	-	-
Q(6)	0.758 (0.979)	8.708 (0.122)	8.22 (0.145)	0.771 (0.978)	7.967 (0.158)	7.856 (0.164)	2.089 (0.836)	2.951 (0.707)
Q(12)	3.682 (0.978)	17.91 (0.084)	18.428 (0.072)	3.695 (0.978)	17.36 (0.098)	18.17 (0.078)	14.29 (0.216)	16.12 (0.138)
LM(4) ^b	4.551 (0.337)	6.882 (0.142)	5.632 (0.228)	4.572 (0.333)	6.531 (0.162)	5.459 (0.243)	5.573 (0.233)	15.66 (0.247)
Q ² (6)	4.934 (0.424)	14.724 (0.012)	9.746 (0.083)	5.007 (0.414)	9.751 (0.083)	8.983 (0.110)	7.751 (0.171)	15.26 (0.333)
Q ² (12)	5.728 (0.891)	17.76 (0.088)	13.021 (0.292)	5.795 (0.887)	13.09 (0.287)	12.34 (0.338)	35.68 (0.000)	40.78 (0.395)
ARCH(4) [‡]	2.875 (0.579)	6.573 (0.161)	6.468 (0.167)	2.871 (0.579)	6.081 (0.193)	6.619 (0.157)	5.455 (0.243)	10.83 (0.213)
SIGN ₁ [†]	1.769 (0.077)	3.796 (0.000)	2.796 (0.005)	0.491 (0.622)	0.453 (0.651)	0.157 (0.875)	-0.226 (0.821)	-1.847 (0.065)
SIGN ₂ [‡]	1.257 (0.287)	5.923 (0.000)	3.553 (0.014)	1.262 (0.285)	5.648 (0.001)	0.682 (0.562)	0.889 (0.455)	4.900 (0.002)

Notes: 1=LOAN_{*t*}, 2=BND_{*t*} and 3=STCK_{*t*}. Sample period 1970:01 - 2012:10. Standard errors in parentheses. * (**) [***] statistically significant at 10% (5%) [1%] level. *a* and *b* coefficients governing DCC matrix. Q(n) and Q²(n) are Ljung-Box statistics for serial correlation up to lag n in the standardized and squared standardized residuals. ^b LM test for serial correlation in standardized residuals up to lag 4. [‡] ARCH LM test for heteroscedasticity in standardized residuals up to lag 4. [†] Engle-Ng's (1993) Sign Bias test for significance of I(ε_{*i,t*}^{*i*} < 0) for i=1,2,3. [‡] Sign Bias test for joint significance of I(ε_{*i,t*}^{*i*} < 0), I(ε_{*j,t*}^{*j*} < 0)ε_{*i,t*}^{*i*} and [1 - I(ε_{*i,t*}^{*i*} < 0)]ε_{*j,t*}^{*j*} for i=1,2,3. I(ε_{*i,t*}^{*i*} < 0) is an indicator variable which takes value 1 if ε_{*i,t*}^{*i*} < 0, and zero otherwise. P-values in parentheses.

Table 6: Seemingly Unrelated Regressions (SUR) estimates of Eq.(8) with $\rho_{23,t}$, $\rho_{12,t}$ and $\rho_{13,t}$ as dependent variable.

	$\rho_{23,t}$	$\rho_{12,t}$	$\rho_{13,t}$
$\rho_{23,t-1}$	0.856*** (0.022)	- (-)	- (-)
$\rho_{12,t-1}$	- (-)	0.806*** (0.015)	- (-)
$\rho_{13,t-1}$	- (-)	- (-)	0.519*** (0.027)
$R_{BCBI,t}$	-0.037 (0.027)	-0.051 (0.070)	-0.040 (0.092)
$R_{S\&P,t}$	0.026* (0.015)	0.049 (0.038)	0.047 (0.051)
ΔLM_t	3×10^{-5} (1×10^{-4})	$4 \times 10^{-4**}$ (2×10^{-4})	$6 \times 10^{-4**}$ (3×10^{-4})
YD_t	$8 \times 10^{-4***}$ (3×10^{-4})	0.002*** (7×10^{-4})	0.003*** (0.001)
$\sigma_{BCBI,t}$	0.094 (0.082)	-0.656*** (0.209)	-0.821*** (0.276)
$\sigma_{S\&P,t}$	-0.114** (0.057)	0.210 (0.140)	0.219 (0.185)
DUM₁	-0.048*** (0.012)	-0.020 (0.030)	-0.083** (0.039)
DUM₂	-0.024* (0.013)	-0.048 (0.032)	-0.075* (0.043)
DUM₃	-0.110*** (0.012)	0.108*** (0.029)	0.132*** (0.039)
Q(6)	4.78 (0.572)	5.667 (0.461)	9.891 (0.129)
Q(12)	7.866 (0.795)	10.09 (0.608)	21.60 (0.042)
LM(4)[†]	1.224 (0.299)	1.521 (0.194)	0.740 (0.564)
Q²(6)	0.735 (0.994)	1.972 (0.992)	9.461 (0.149)
Q²(12)	1.512 (0.998)	8.346 (0.752)	14.31 (0.281)
ARCH(4)[‡]	0.108 (0.979)	0.114 (0.972)	2.208 (0.067)
ADF[§]	22.33 (0.000)	19.52 (0.000)	20.07 (0.000)
R²	0.770	0.871	0.504

Notes: 1=LOAN_t, 2=BND_t and 3=STCK_t. Sample period 1970:01 - 2012:10. Constant terms not reported. * (**) [***] statistically significant at 10% (5%) [1%] level. Standard errors in parentheses. Q(n) and Q²(n) are Ljung-Box statistics for serial correlation in residuals and squared residuals up to lag n. [†] LM test for serial correlation in residuals up to lag 4. [‡] ARCH LM test for heteroscedasticity in residuals up to lag 4. P-values in parentheses. Adjusted R² calculated as $1 - (1 - R^2)/(T - 1/T - k)$. [§] Augmented Dickey-Fuller test applied to residuals.

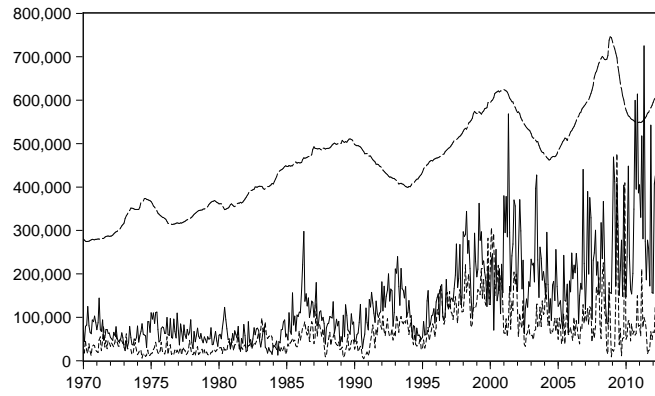


Fig. 1: Average volumes of outstanding C&I loans ($LOAN_t$, dashed line), and of issuance of corporate bonds (BND_t , solid line) and stocks ($STCK_t$, dotted line) re-scaled by multiplying the monthly data by the number of months correspondent to the average maturity of C&I loans (15 months). Series in millions of US dollars.

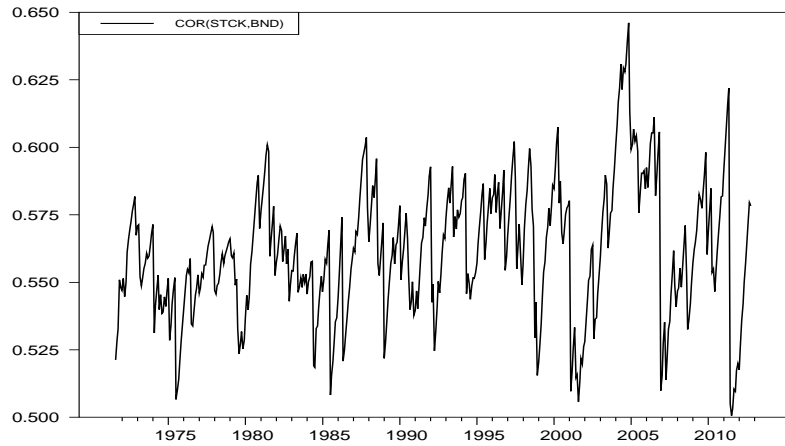


Fig. 2: Conditional correlation between BND_t and $STCK_t$.

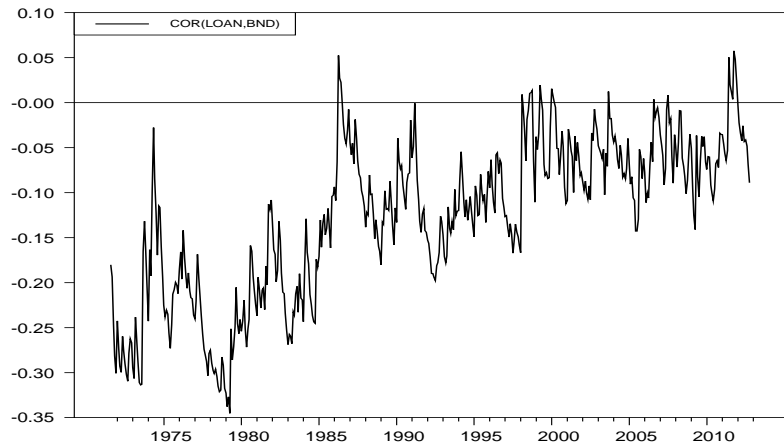


Fig. 3: Conditional correlation between $LOAN_t$ and BND_t .

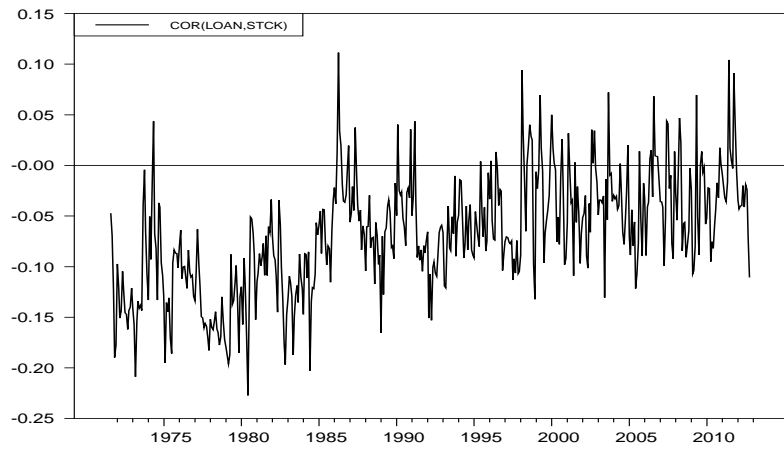


Fig. 4: Conditional correlation between $LOAN_t$ and $STCK_t$.

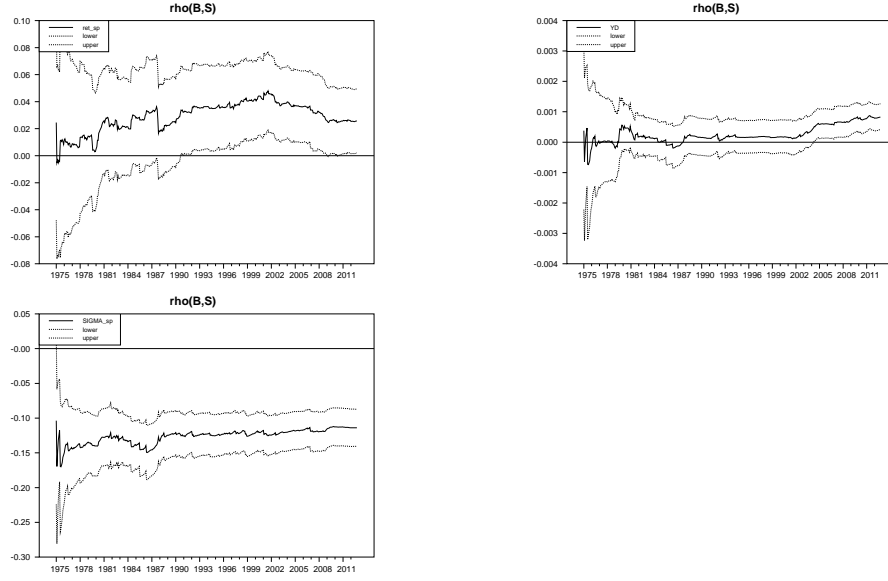


Fig. 5: Estimates of the time-varying parameters $b_{2,t}$, $b_{4,t}$ and $b_{6,t}$ (solid lines) of Eq.(8) with $\rho_{23,t}$ as dependent variable, and upper and lower bounds (dotted lines) of 95% confidence intervals.

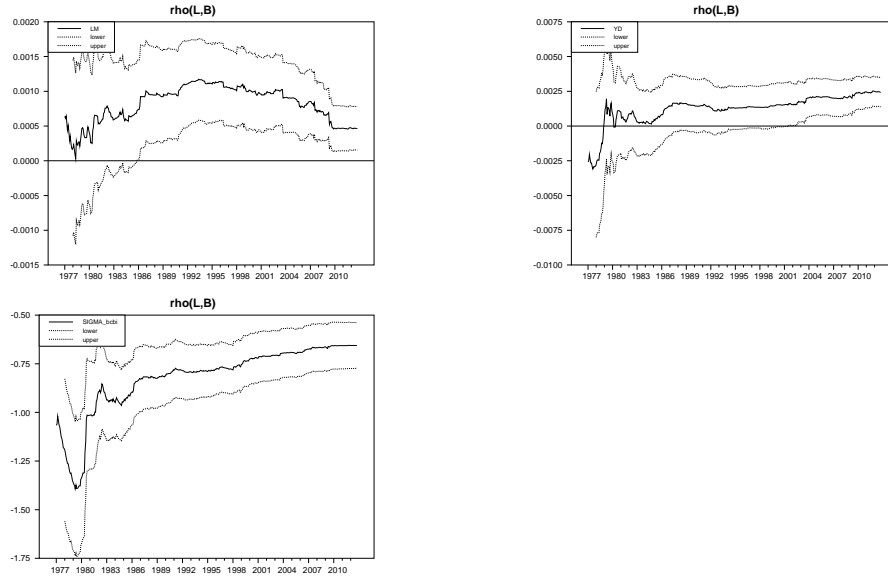


Fig. 6: Estimates of the time-varying parameters $b_{3,t}$, $b_{4,t}$, and $b_{5,t}$ (solid lines) of Eq.(8) with $\rho_{12,t}$ as dependent variable, and upper and lower bounds (dotted lines) of 95% confidence intervals.

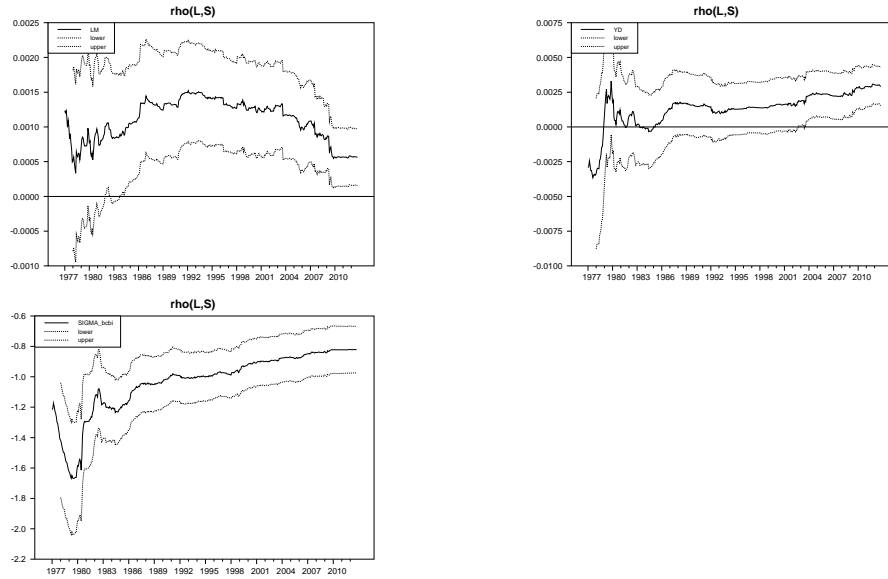


Fig. 7: Estimates of the time-varying parameters $b_{3,t}$, $b_{4,t}$, and $b_{5,t}$ (solid lines) of Eq.(8) with $\rho_{13,t}$ as dependent variable, and upper and lower bounds (dotted lines) of 95% confidence intervals.

References

- Allen, F. and D. Gale (1997, June). Financial markets, intermediaries, and intertemporal smoothing. *The Journal of Political Economy* 105(3), 523–546.
- Andrews, D. W. (1991). Heteroscedasticity and autocorrelation consistent covariance matrix estimation. *Econometrica* 59, 817–854.
- Baele, L., G. Bekaert, and K. Inghelbrecht (2010, June). The determinants of stock and bonds return comovements. *The Review of Financial Studies* 23(6), 2374–2428.
- Baker, M. and J. Wurgler (2012, June). Comovement and predictability relationships between bonds and the cross-section of stocks. *Review of Asset Pricing Studies* 2(1), 57–87.
- Beetsma, R. and M. Giuliodori (2012). The changing macroeconomic response to stock market shocks. *Journal of Macroeconomics* 34, 281 – 293.
- Bloom, N. (2009). The impact of uncertainty shocks. *Econometrica* 77, 623 – 685.
- Brenner, M., P. Pasquariello, and M. Subrahmanyam (2009, December). On the volatility of comovements of U.S. financial markets around macroeconomic news announcements. *The Journal of Financial and Quantitative Analysis* 44(6), 1265–1289.

- Campbell, J., M. Lettau, B. G. Malkiel, and Y. Xu (2001). Have individual stocks become more volatile? An empirical exploration of idiosyncratic risk. *Journal of Finance* 56, 1 – 43.
- Campbell, J. Y. and J. Ammer (1993, March). What moves the stock and bond market? A variance decomposition for long-term asset returns. *The Journal of Finance* 48(1), 3–37.
- Casalin, F. and E. Dia (2009). Financial market volatility and primary placements. *Economic Letters* 105, 284–286.
- Casalin, F. and E. Dia (2013). Security issuance and the business cycle. *Economics Bulletin* 33(3), 1751–1761.
- Casalin, F. and E. Dia (2014). Adjustment costs, financial frictions and aggregate investment. *The Journal of Economics and Business* 75, 60–79.
- Chordia, T., A. Sarkar, and A. Subrahmanyam (2005, January). An empirical analysis of stock and bond market liquidity. *The Review of Financial Studies* 18(1), 85–129.
- Connolly, R., C. Stivers, and L. Sun (2005, March). Stock market uncertainty and the stock-bond return relation. *The Journal of Financial and Quantitative Analysis* 40(1), 161–194.
- Connolly, R., C. Stivers, and L. Sun (2007). Commonality in time variation of stock-stock and stock-bond return comovements. *Journal of Financial Markets* 10, 192 – 218.

- De Fiore, F. and H. Uhlig (2011, October). Bank finance versus bond finance. *Journal of Money, Credit and Banking* 43(7), 1399–1421.
- Dixit, A. K. and R. S. Pindyck (1994). *Investment under Uncertainty*. Princeton University Press.
- Engle, R. F. (2002). Dynamic conditional correlation: A simple class of multivariate GARCH models. *Journal of Business and Economic Statistics* 20, 339–350.
- Engle, R. F. and K. F. Kroner (1995). Multivariate simultaneous generalized ARCH. *Econometric Theory* 11, 122–150.
- Engle, R. F. and V. Ng (1993). Measuring and testing the impact of news on volatility. *Journal of Finance* 48, 1479–1778.
- Giles, D. E. and R. T. Godwin (2012). Testing for multivariate cointegration in the presence of structural breaks: P-values and critical values. *Applied Economics Letters* 19, 1561–1565.
- Glosten, L. R., R. Jaganathan, and D. E. Runkle (1993). On the relation between the expected value and the volatility of the normal excess return on stocks. *The Journal of Finance* 48, 1779–1801.
- Goyenko, R. Y. and A. D. Ukhov (2009, February). Stock and bond market liquidity: A long-run empirical analysis. *The Journal of Financial and Quantitative Analysis* 44(1), 189–212.

- Graham Elliott, T. R. and J. H. Stock (1996). Efficient tests for an autoregressive unit root. *Econometrica* 64, 813–836.
- Gregory, A. and B. E. Hansen (1996). Residual-based tests for co-integration in model with regime switching. *Journal of Econometrics* 70, 99 – 126.
- Hansen, B. E. (1992). Tests for parameter instability in regression with I(1) processes. *Journal of Business and Economic Statistics* 10, 321 – 335.
- Johansen Søren, R. M. and B. Nielsen (2000). Cointegration analysis in the presence of structural breaks in the deterministic trend. *Econometrics Journal* 3, 216–249.
- Kashyap, A. K., O. A. Lamont, and J. C. Stein (1994, August). Credit conditions and the cyclical behaviour of inventories. *The Quarterly Journal of Economics* 109(3), 565–592.
- Kashyap, A. K., J. C. Stein, and D. W. Wilcox (1993, March). Monetary policy and credit conditions: Evidence from the composition of external finance. *The American Economic Review* 83(1), 78–98.
- Lemmon, M. and M. R. Roberts (2010, June). The response of corporate financing and investment to changes in the supply of credit. *The Journal of Financial and Quantitative Analysis* 45(3), 555–587.
- Lin, R. Engle, and K. Ito (1994). Do bulls and bears move across borders? International transmission of stock returns and volatility. *Review of Financial Studies* 7, 507–538.

- Ng, S. and P. Perron (2001). Length lag selection and the construction of unit root tests with good size and power. *Econometrica* 69, 1519 – 1554.
- Park, J. Y. (1992). Canonical cointegrating regressions. *Econometrica* 60, 119–143.
- Phillips, P. C. and B. E. Hansen (1990). Statistical inference in instrumental variables regression with I(1) processes. *Review of Economic Studies* 57, 99 – 125.
- Phillips, P. C. and S. Ouliaris (1990). Asymptotic properties of residual based tests for cointegration. *Econometrica* 58, 165 – 193.
- Reilly, F. K., D. J. Wright, and J. A. Gentry (2009). Historic changes in the high yield bond market. *Journal of Applied Corporate Finance* 21(3), 65–79.
- Russ, K. N. and D. Valderrama (2012, September). A theory of bank versus bond finance and intra-industry reallocation. *The American Economic Review* 34(3), 652–673.
- Schwert, G. W. (1989). Business cycles, financial crises and stock volatility. *Carnegie-Rochester Conference Series on Public Policy* 31, 83–125.
- Schwert, G. W. (2002). Stock volatility in the new millennium: How wacky is Nasdaq? *Journal of Monetary Economics* 49, 3–26.
- Scruggs, J. T. and P. Glabadanidis (2003, June). Risk premia and the dynamic covariance between stock and bond returns. *The Journal of Financial and Quantitative Analysis* 38(2), 295–316.

- Stock, J. H. and M. W. Watson (1993). A simple estimator of cointegrating vectors in higher order integrated system. *Econometrica* 61, 783–820.
- Syllignakis, M. and G. Kouretas (2011). Dynamic correlation analysis of financial contagion: Evidence from the central and eastern european markets. *International Review of Economics and Finance* 20, 717–732.
- Taggart, R. A. (1987). The growth of the "Junk" bond market and its role in financing takeovers. In A. J. Auerbach (Ed.), *Mergers and Acquisitions*, pp. 5–24. Chicago: University of Chicago Press.
- Wang, P. and T. Moore (2008). Stock market integration for the transition economies: Time-varying conditional correlation approach. *The Manchester School*, 116 – 133.